RISK CONTROL

ESG and Credit Rating Correlations

Presentation by William Perraudin

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1. Introduction
2. ESG and Credit ratings data
3. Statistical methods for rating analysis
4. Results
5. Conclusions

Introduction (1/2)

- Banks worldwide are implementing new approaches to measuring risk associated with the Environmental, Social and Governance features of their loan exposures. ESG adds an additional dimension of risk to the drivers that banks have traditionally considered: credit, market and operational.
- This paper develops a new approach to modelling ESG and credit risk within a common framework. The technique involves modelling ESG and credit ratings as correlated Markov chains, expanding the classic Ordered Probit approach to credit portfolio analysis by including an additional metric of issuer ESG status.
- The models proposed are implemented statistically using historical data on Refinitiv (ESG) and Moody's (credit) ratings. The parameter estimations are performed using Maximum Likelihood techniques. The model allows for correlation between common factors driving credit and ESG ratings and for correlation between issuer-level idiosyncratic shocks.

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Introduction (2/2)

- Individual issuer ratings exhibit relatively low correlations (lower than those assumed in the Basel Internal Ratings Based Approach risk weights, for example). But a high and statistically significant correlation is evident between the common factors driving, respectively, credit and ESG ratings.
- This suggests that, in a diversified bank portfolio, ESG and credit factors will jointly boost overall risk through their positively correlated common movements.
- As a final exercise, we repeat the analysis but using E, S and G ratings (which we construct from the Refinitiv pillar scores) rather than the official Refinitiv ESG rating. This permits us to examine which aspects of the ESG ratings are correlated with credit ratings. In this, we find that the credit risk factor correlations are strongest with Environment and lowest with Governance.

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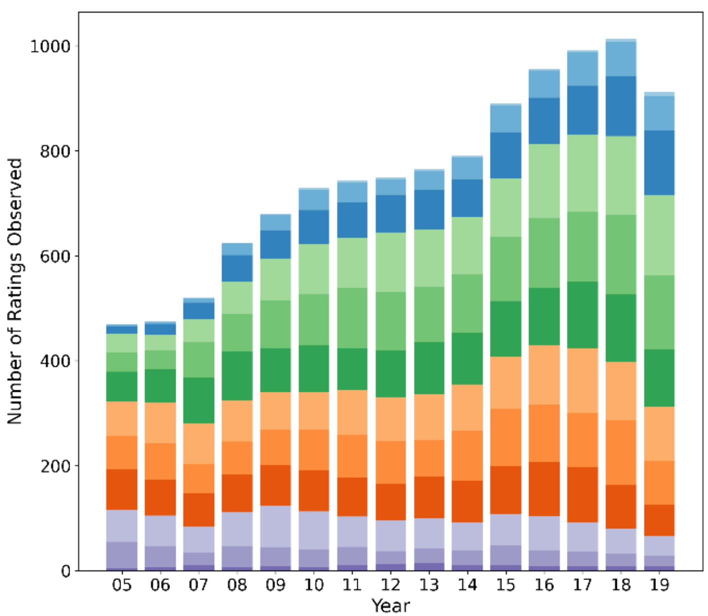
ESG and Credit Ratings Data (1/4)

- The ESG dataset covers 8,473 firms across 84 domiciles (countries), 5 regions and 11 economic sectors.
- The dataset offers several identifiers as well as ESG scores, such as industry group and ISINs, ranging from 2002 until 2019.
- A Refinitiv ESG rating consists of a score between 0 and 100. The numerical scores are converted into one of 12 letter grades from D- to A+, hereafter referred to as ESG ratings, using a set of cut-off points.
- For example, a D- rated company would have a score between 0 and 100/12, while a D rated company would have a score between 100/12 and 100/6, and so on.
- Refinitiv also provides individual E, S and G scores, constructed in a similar way, for each year. Here, we focus only on the overall ESG score.

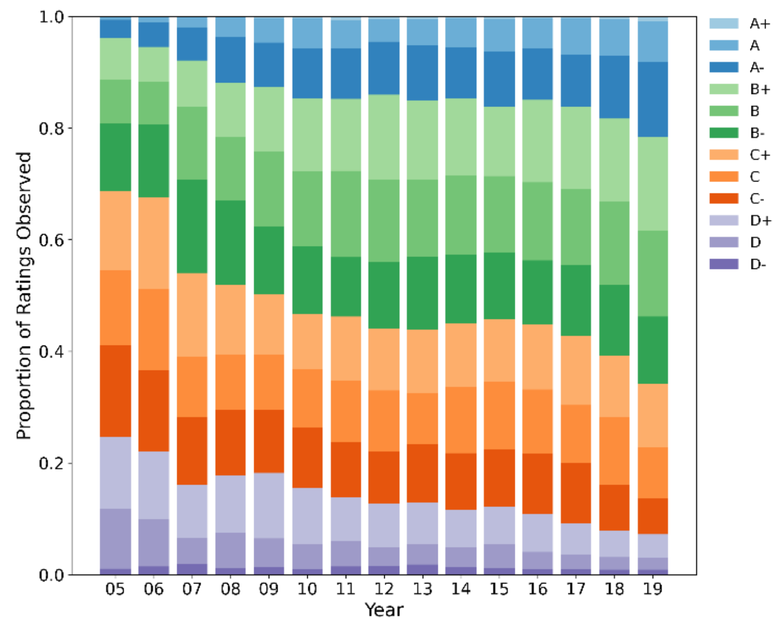
ESG and Credit Ratings Data (2/4)

- The figure displays the distribution of ESG ratings by year, by number in Panel a) and by proportion in Panel b). For the purposes of evaluating more general transitions, we also consider the case of 4 ESG quartile letter ratings – A, B, C, D.
- Refinitiv ESG Ratings Conditional on Having a Moody's Credit Rating

Panel a) By number

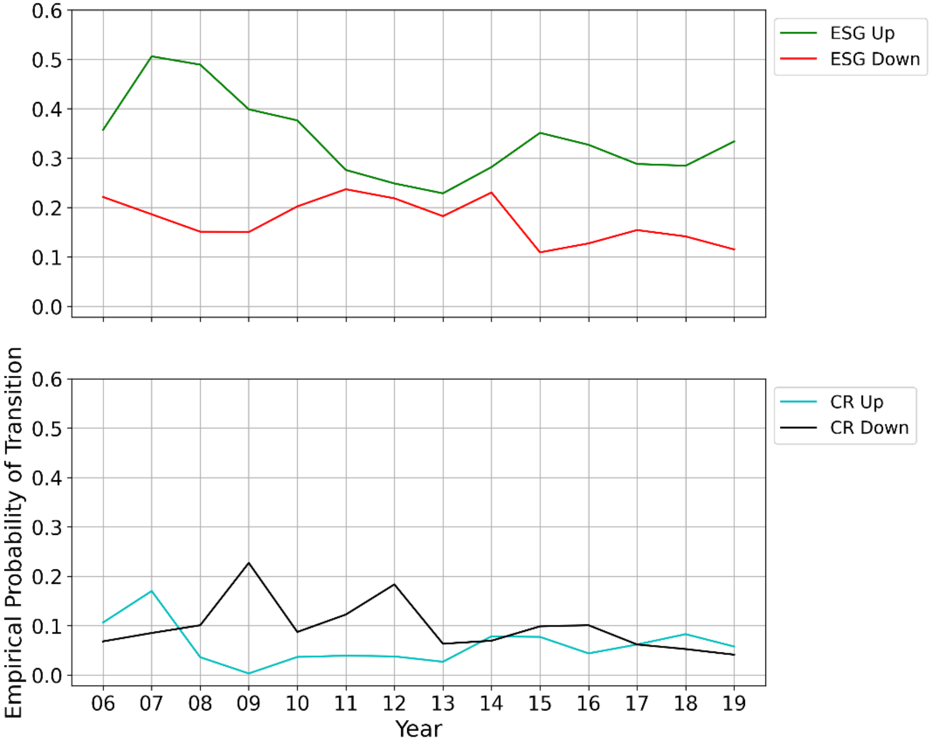


Panel b) By proportion



ESG and Credit Ratings Data (3/4)

- We conduct exploratory analysis of ESG and Credit ratings.
- The figure shows the evolution over time of empirical rating upgrade and downgrade probabilities.
- The ESG ratings in the sample generally upgrade more than downgrade, but when the proportion of upgrades declined, the proportion of downgrades increased, and likewise fell again once the proportion of upgrades increased after 2013.



- We see a similar pattern in credit ratings transitions, as they seem negatively correlated before remaining fairly constant after 2013.
- These patterns are consistent with there being common factors separately driving the credit and ESG ratings.

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ESG and Credit Ratings Data (4/4)

Transition	ESG Up	ESG No Change	ESG Down	CR Up	CR No Change	CR Down
ESG Up	1.0000	-0.8648	-0.2170	0.3695	-0.4223	0.1047
ESG No Change	-0.8648	1.0000	-0.3025	-0.4102	0.5248	-0.1694
ESG Down	-0.2170	-0.3025	1.0000	0.0961	-0.2186	0.1305
CR Up	0.3695	-0.4102	0.0961	1.0000	-0.3570	-0.4624
CR No Change	-0.4223	0.5248	-0.2186	-0.3570	1.0000	-0.6632
CR Down	0.1047	-0.1694	0.1305	-0.4624	-0.6632	1.0000

Note: Pearson product-moment correlation coefficients for the yearly proportions of rating transitions that were upgrades, downgrades or did not change for ESG and credit ratings. ESG Up/Down refer to ESG upgrades/downgrades and similarly for credit rating.

- The table presents the correlations for time series of upgrade and downgrade rates (i.e., empirical probabilities of upgrade and downgrade) for ESG and credit ratings.
- The most relevant results are the 36.95% and 13.05% correlations between upgrades and downgrades, respectively, in credit and ESG ratings.
- This suggests that the common factors driving ESG and credit ratings are positively correlated.

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Statistical Methods (1/4)

- We assume that ratings evolve as correlated Markov chains. Each issuer's rating, both for ESG status and credit standing, stays constant or moves to a different value with probabilities specified in rating transition matrices which are constant over time.
- For both ESG and credit ratings, we formulate the Markov chain using an Ordered Probit approach, also commonly referred to as the Creditmetrics model. This permits one to allow for correlation between rating transitions of different issuers.
- We assume that a single common factor drives credit rating transitions but that this factor can be correlated with another single factor that drives ESG rating transitions.
- We are interested in the degree of correlation between the two common factors as this is potentially material for risk in a well-diversified bank portfolio with credit and ESG risk.

Statistical Methods (2/4)

- Our implementation yields three models embodying the following assumptions:

  Model 1 – Independent idiosyncratic shocks and correlated common factors

  Model 2 – Independent common factors and correlated idiosyncratic shocks

  Model 3 – Correlated common factors and idiosyncratic shocks, i.e., the “full model”.

- We fit each model for each of 8 cases. The eight cases correspond to three binary choices that we make:

  1. Employ either 12 or 4 ESG quartile letter ratings,
  2. Use different weightings for yearly observations,
  3. Employ either all credit rating transitions or only transitions that start in investment grade.

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Statistical Methods (3/4)

- We assume the latent variable $\hat{X}_{n,t}^{(C)}$ drives the credit rating following one factor structure:

$$\hat{X}_{n,t}^{(C)} = \sqrt{\rho^{(C)}} f_t^{(C)} + \sqrt{1 - \rho^{(C)}} \epsilon_{n,t}^{(C)}$$

- Here $f_t^{(C)}$, a common factor for year t, and $\epsilon_{n,t}^{(C)}$, firm n's idiosyncratic shock for year t, are standard normal.
- Similarly, we model $\hat{X}_{n,t}^{(E)}$ that drives ESG rating as:

$$\hat{X}_{n,t}^{(E)} = \sqrt{\rho^{(E)}} f_t^{(E)} + \sqrt{1 - \rho^{(E)}} \epsilon_{n,t}^{(E)}$$

- The evolution of rating changes follows a bivariate Markov Chain with transition matrices $M^{(C)}$ and $M^{(E)}$.
- For our first model, we assume that the factors $f^{(C)}$ and $f^{(E)}$ have a correlation coefficient ρ.
- We now have the likelihood of observing the historical ratings experience of both credit and ESG rating, given ρ:

Statistical Methods (4/4)

- Denote by $N^{(C)}(i,j,t)$, the number of observations for which a credit rating goes from i to j for a firm between the years t and $t+1$, and similarly $N^{(E)}(i,j,t)$ for ESG ratings.
- For our first model, we assume that the factors $f^{(C)}$ and $f^{(E)}$ have a correlation coefficient ρ. We now have the likelihood of observing the historical ratings experience of both credit and ESG rating, given ρ:

$$L(\rho) \equiv \prod_{t=0}^{T} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left\{ \prod_{R=E,C} \prod_{i=1}^{J^{(R)}} \left\{ \Phi\left(\frac{z_{i,1}^{(R)} - \sqrt{\rho^{(R)}} f_t^{(R)}}{\sqrt{1-\rho^{(R)}}}\right)^{N^{(R)}(i,1,t)} \times \left\{ \prod_{j=2}^{J^{(R)}-1} \left(\Phi\left(\frac{z_{i,j}^{(R)} - \sqrt{\rho^{(R)}} f_t^{(R)}}{\sqrt{1-\rho^{(R)}}}\right) - \Phi\left(\frac{z_{i,j-1} - \sqrt{\rho^{(R)}} f_t^{(R)}}{\sqrt{1-\rho^{(R)}}}\right)\right)^{N^{(R)}(i,j,t)} \right\} \times \left(1 - \Phi\left(\frac{z_{i,J^{(R)}-1}^{(R)} - \sqrt{\rho^{(R)}} f_t^{(R)}}{\sqrt{1-\rho^{(R)}}}\right)\right)^{N^{(R)}(i,J^{(R)},t)} \right\} \right\} \phi\left(f_t^{(C)}, f_t^{(E)} \middle| \rho\right) df_t^{(C)} df_t^{(E)}$$

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Results (1/4)

- This section presents the results of the statistical analysis. As explained above, we estimate three models under eight different sets of assumptions (so, 24 models in all). The eight sets of assumptions correspond to the possible values of three binary choices:

  1. Whether to use Refinitiv's suggested 12 ESG quantiles or use 4 ESG categories,
  2. Whether each year should be weighted equally in our transition matrix calculation and
  3. Whether all ratings data should be employed or just observations that start in an investment grade rating category.

- Recall that the three models correspond to the cases in which

  (a) Common factors are correlated across credit and ESG ratings but idiosyncratic shocks are uncorrelated,

  (b) Common factors are uncorrelated across rating types but idiosyncratic shocks are correlated with any given time period for any given issuer, and

  (c) The full model in which both types of correlation are included.

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Results (2a/4)

Assumption	Parameter	Estimate	StD Error	t-Statistic
12 ESG quantiles, years weighted by observations	Credit Rating Factor Weight	0.0543	0.0154	3.5226
	ESG Rating Factor Weight	0.0214	0.0086	2.4968
	Model 1: Credit-ESG Factor Correlation	0.2800	0.2689	1.0413
	Model 2: Idiosyncratic Shock Correlation	0.0223	0.0200	1.1120
	Model 3: Full Model Factor Correlation	0.2826	0.7661	0.3689
	Model 3: Full Model Shock Correlation	0.0222	0.0221	1.0021
12 ESG quantiles, years weighted equally	Credit Rating Factor Weight	0.0623	0.0171	3.6411
	ESG Rating Factor Weight	0.0606	0.0233	2.6071
	Model 1: Credit-ESG Factor Correlation	0.3793	0.3265	1.1617
	Model 2: Idiosyncratic Shock Correlation	0.0251	0.0203	1.2358
	Model 3: Full Model Factor Correlation	0.3893	0.3181	1.2238
	Model 3: Full Model Shock Correlation	0.0252	0.0201	1.2578
4 ESG quantiles, years weighted by observations	Credit Rating Factor Weight	0.0543	0.0154	3.5226
	ESG Rating Factor Weight	0.0159	0.0078	2.0321
	Model 1: Credit-ESG Factor Correlation	0.3807	0.2791	1.3638
	Model 2: Idiosyncratic Shock Correlation	0.0207	0.0252	0.8212
	Model 3: Full Model Factor Correlation	0.3524	0.3160	1.1153
	Model 3: Full Model Shock Correlation	0.0204	0.0375	0.5440
4 ESG quantiles, years weighted equally	Credit Rating Factor Weight	0.0623	0.0171	3.6411
	ESG Rating Factor Weight	0.0246	0.0157	1.5646
	Model 1: Credit-ESG Factor Correlation	0.4174	0.2981	1.4001
	Model 2: Idiosyncratic Shock Correlation	0.0243	0.0256	0.9488
	Model 3: Full Model Factor Correlation	0.3710	0.3392	1.0940
	Model 3: Full Model Shock Correlation	0.0242	0.0255	0.9471

For ALL firms, the Table displays results based on use of 12 and 4 ESG categories and with two different weighting approaches for the transition matrix estimation, i.e., four sets of results in all.

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Results (2b/4)

Assumption	Parameter	Estimate	StD Error	t-Statistic
12 ESG quantiles, years weighted by observations	Credit Rating Factor Weight	0.0567	0.0162	3.5029
	ESG Rating Factor Weight	0.0198	0.0083	2.3829
	Model 1: Credit-ESG Factor Correlation	0.3374	0.2628	1.2841
	Model 2: Idiosyncratic Shock Correlation	0.0231	0.0203	1.1367
	Model 3: Full Model Factor Correlation	0.3200	0.3424	0.9347
	Model 3: Full Model Shock Correlation	0.0230	0.0216	1.0612
12 ESG quantiles, years weighted equally	Credit Rating Factor Weight	0.0676	0.0183	3.6853
	ESG Rating Factor Weight	0.0518	0.0246	2.1091
	Model 1: Credit-ESG Factor Correlation	0.4455	0.2881	1.5462
	Model 2: Idiosyncratic Shock Correlation	0.0242	0.0212	1.1373
	Model 3: Full Model Factor Correlation	0.3928	0.4004	0.9809
	Model 3: Full Model Shock Correlation	0.0242	0.0297	0.8169
4 ESG quantiles, years weighted by observations	Credit Rating Factor Weight	0.0567	0.0162	3.5029
	ESG Rating Factor Weight	0.0150	0.0077	1.9563
	Model 1: Credit-ESG Factor Correlation	0.5173	0.2490	2.0779
	Model 2: Idiosyncratic Shock Correlation	0.0253	0.0263	0.9606
	Model 3: Full Model Factor Correlation	0.5141	0.2472	2.0799
	Model 3: Full Model Shock Correlation	0.0248	0.0259	0.9583
4 ESG quantiles, years weighted equally	Credit Rating Factor Weight	0.0676	0.0183	3.6853
	ESG Rating Factor Weight	0.0205	0.0125	1.6346
	Model 1: Credit-ESG Factor Correlation	0.5562	0.2458	2.2628
	Model 2: Idiosyncratic Shock Correlation	0.0271	0.0268	1.0134
	Model 3: Full Model Factor Correlation	0.5549	0.2385	2.3267
	Model 3: Full Model Shock Correlation	0.0267	0.0256	1.0435

For firms that start in INVESTMENT GRADE, the Table displays results based on use of 12 and 4 ESG categories and with two different weighting approaches for the transition matrix estimation, i.e., four sets of results in all.

Results (3/4)

- The estimated factor weights (i.e., the correlations for pairs of credit ratings or pairs of ESG ratings) appear relatively low, for example, 6.23% and 2.46% are the credit and ESG factor weights, respectively (with equally weighted transition matrices and 4 ESG rating categories). (For IG firms, the values are 6.76 and 2.05.)
- The credit risk factor weights may be compared to the factor correlations employed within the Basel Internal Ratings Based Approach corporate risk weight formula which range from 12% to 24% depending on the default probability of the firm in question.
- While the latent variables driving ratings for individual exposures have low weights (as just noted), the correlation between the ESG and the credit common factors are high, being, for all credit grades (see the table), 41.74% for Model 1 in the case of equally weighted transition matrices and 4 ESG rating categories, and 37.10% in Model 3 (the “full model”).
- For investment grade firms alone, the equivalent figures are 55.62% and 55.49%.

Results (4/4)

- The idiosyncratic shock correlation is small, being, for all credit grades 2.43% in Model 2 and 2.42% in Model 3 when equally weighted transition matrices and 4 ESG rating categories are employed. The equivalent for IG firms are 2.71% and 2.67%.
- Comparing the results with all credit grade firms to those for Investment Grade firms alone, one may observe that the factor correlations are higher and significance levels greater.
- So, for example, for 4 ESG quantiles with equally weighted years, the Credit-ESG factor correlation is 55.62% for all firms with a t-statistic of 2.26 compared to 41.74% for IG firms with a t-statistic of 1.40.
- This finding is intuitive since the presence of sub-investment grade borrowers probably injects noise into the estimation, reducing the precision of estimates.

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Conclusions (1/2)

- Different approaches may be taken to integrating ESG risk with other types of risk within a risk framework:

1. Some view ESG risk as a sub-category of credit risk (or more generally of payoff-performance risk for financial assets including equities) contributing to risk to the extent that it influences default likelihood or the Loss Given Default rate.
   - In this case, one might argue that the correct adjustment for a bank's risk management framework is to include ESG indicators within existing credit scorecards.
   - One may note that governance indicators are already included in many bank credit rating scorecards while environmental or 'transition' risk may or may not be included. (If, as is common, a one-year horizon is employed for risk management, the bank may consider that transition risk contributes little to pure default risk.)
   - Social risk rarely figures in bank credit scorecards.
2. On the other hand, some argue that ESG affects the market pricing of debt instruments *even allowing for* such indicators of payoff risk as credit ratings (which may be taken to describe the payoff distribution of the exposures). This may be because ESG affects risk premia on debt instruments or because investors view high ESG scores as a 'merit good' and, hence, bid up prices even if the value of ESG as reflected in Expected or Unexpected Losses.

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Conclusions (2/2)

- The approach taken in this paper, represents a coherent response to ESG risk management for any case in which ESG factors affect market pricing over and above traditional credit ratings.
- One may analyse combined credit and ESG risk by modelling the joint behaviour of credit and ESG ratings, extending the standard Ordered Probit (or Creditmetrics) model, to two dimensions of risk and then calculating the impact on the value of the portfolio in question, applying spreads conditional on credit and ESG ratings.
- In a companion paper, to be issued shortly, we show that ESG is, indeed, reflected in the market pricing of publicly traded bonds, allowing for credit status as registered by credit ratings and, hence, we provide the other element necessary to the full implementation of this risk management approach.
- Thus, our paper represents a step in the construction of appropriate risk tools for a world in which banks and others wish to allow for ESG risk.

Contact

Website: www.riskcontrollimited.com
Telephone: +44 20 3307 0730
Address: 13-14 Dean Street, London, W1D 3RS, U.K.

William Perraudin, Director
+44 20 3307 0731 (o) +44 7968 328 459 (m)
william.perraudin@riskcontrollimited.com